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A two-layer predictive control for hybrid electric vehicles energy management

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Abstract: In this paper, a two-layer predictive energy management strategy for hybrid electric vehicles without an external recharge is introduced. The low-level layer exploits telemetry data over a short-term horizon in a model predictive control structure that provides the engine torque, but also the stop-start decision. The upper layer uses a tuning mechanism with a longer horizon to calculate the MPC weighting factor that ensures a balance between the fuel and battery consumption. An analysis of this upper-level tuning prediction horizon dependence on the drive cycle characteristics is performed. The robustness with respect to state-of-charge and engine torque estimation is also proven by a sensitivity analysis.

Keywords: hybrid electric vehicle, energy management, predictive control

1. INTRODUCTION

Fuel consumption optimization is a priority objective in the automotive research, whose development during the last years has witnessed an increased interest in hybrid vehicles. The research work spans several fields related to this topic: topology, dimensioning, modeling and control. The latter tackles especially the energy management problem, which refers to the power distribution between the engine and the additional power source.

There are currently numerous techniques in the literature for the power distribution problem: dynamic programming (off-line solution, it needs the entire drive cycle), rule-based (Goerke et al., 2015), *Equivalent Consumption Minimization Strategy* (ECMS), with its different approaches, such as Adaptive-ECMS (Musardo et al., 2005) and Telemetric-ECMS (Sciarretta et al., 2004). Model predictive control (MPC) has gained in popularity during the last years, it its deterministic form (Cairano et al., 2011), (Lu et al., 2013) or stochastic (Ripaccioli et al., 2010), (Josevski and Abel, 2014).

Current technologies allow the acquisition of future traffic data and consequently, their exploitation within predictive control strategies, with explicit reconstruction of the speed profile or by the use of pattern recognition (drive cycle profile, driving style). In (Bender et al., 2014) the future target speed is reconstructed from the vehicle current position and a database, whereas in (Mayr et al., 2011) a cycle detection based on correlation analysis is performed. The ability to capture transient characteristics, such as abrupt changes, makes the frequency analysis a suitable approach: in (Wang et al., 2012) a wavelet-based analysis is used for feature extraction from accelerometer data, whereas in (Liu et al., 2015) a metric that characterizes speed fluctuations is defined using Fourier analysis.

This paper continues the previous work (Stroe et al., 2016b), where an MPC - based torque split optimization including stop-start mechanism has been introduced. It is assumed that the vehicle speed can be foreseen up to several kilometers and this prediction will be incorporated into a two-layer control structure, that work with longer horizons for the higher decision layers. The low-level controller handles the power distribution, which is reduced to torque calculation in the absence of gearshift optimization, and also the stop-start command. This problem is formulated as an MPC optimization, whose tuning parameter is calculated at the upper level, that uses a long-term prediction. The main contribution of this paper is to present a method to calculate the penalty factor in the MPC design as a sum of an average-based feedforward component, calculated over a prediction horizon, and a SOC feedback corrective term. The influence of the prediction horizon on fuel gain is analysed for different drive cycles. The robustness with respect to torque and SOC estimation is equally performed in order to complete the sensitivity analysis of the proposed structure.

The paper is organized as follows: first, a powertrain control-oriented model is introduced and next, an MPC formulation is presented, for the torque distribution and ICE stop-start, with a focus on the MPC tuning method. The performance and robustness of the proposed strategy are evaluated into a model-in-the-loop validation.

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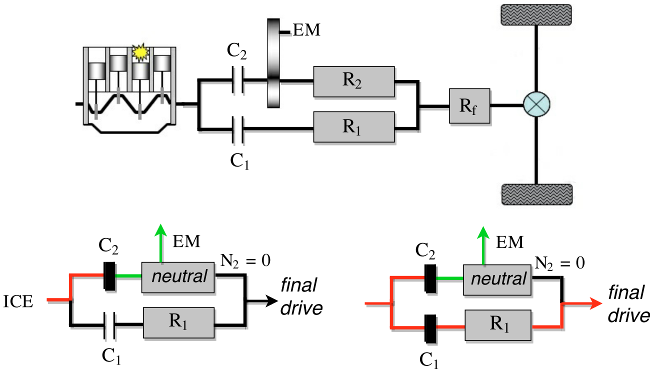
NOTATIONS

- ICE - Internal Combustion Engine
- EM - Electric Machine
- DCT - Dual-Clutch Transmission
- $\mathrm{R_i}$ - gear ratio engaged on i^{th} shaft (includes neutral definition), $i \in \{1 : odd, 2 : even\}$
- $\mathrm{C_i}$ - clutch status (0 - open, 1 - closed)
- $N_i = \min(R_i, 1)$ - used to define the case where one of the shafts is decoupled
- $R_{f(R_i)}$ - axle ratio corresponding to ith shaft
- $r^w_{ice/em}$ - ratio between the ICE/EM torque at wheel level and the component (ICE/ EM) torque
- rat_{em} - ratio between the EM and the corresponding shaft where it is connected
- ω^{ctrl}_{ice} - idle speed or 0 rpm, in case of engine stop
- R_w - wheel radius

2. POWERTRAIN CONTROL-ORIENTED MODEL



Charge during standstill

Charge during driving

Fig. 1. DCT hybrid configuration

Vehicle dynamics is expressed using a backward approach, where the reference speed and acceleration are known and from which the required torque can be determined. Hence, the wheel torque demand can be calculated from the velocity (v), environment data, such as slope (α), air density (ρ_{air}) and vehicle parameters, such as the mass (m), frontal area (A_f), aerodynamic drag coefficient (c_d), rolling friction coefficients (c_{r0}, c_{r1}):

$$T_w = \Big(\frac{1}{2}\rho_{air}A_f c_d v^2 + (c_{r1}v + c_{r0})mgcos(\alpha) \\ + mgsin(\alpha) + m\dot{v}\Big)R_w \quad (1)$$

A wheel level supervisory control is the most appropriate for an HEV, where the EM can be connected to different driveline positions. Shafts inertias and clutch dynamics are neglected and, therefore, a static model for torque and rotational speeds of the components is introduced, as in (2)-(6). The purpose of the model is to define a relation between the components torques and the total torque demand and for the rotational speeds, a dependence of velocity and driveline states (clutches states and gear engaged).

The architecture considered here is a dual-clutch transmission hybrid with the EM connected to the even primary shaft, as in Fig. 1. In (Stroe et al., 2016a) it was shown that with a proper parametrization, this configuration can represent all types of hybrid parallel architectures. For a better understanding of the system and of the proposed model, Table 1 summarizes the clutches states with respect to functional modes. The variable N_2 is introduced in order to correctly define special cases when one of the shafts is decoupled from the wheel (to charge the battery via the ICE at standstill or during driving, with odd gear engaged). For the present configuration, only the even shaft is concerned, due to EM position. The engine is disconnected from the drive not only for the case when $C_1 = C_2 = 0$, but also for the charge at standstill, where $C_2 = 1$, but $N_2 = 0$. Therefore, the ICE speed will be defined by ω^{ctrl}_{ice} when $C_1 + N_2C_2 = 0$, as expressed in (5).

Table 1. Hybrid DCT modes as functions of clutches states and N_2

C_1	C_2	N_2	*Case*
0	0	0	standstill, sailing
0	0	1	electric driving, regenerative braking
0	1	1	hybrid or conventional, even gear engaged
0	1	0	charge during standstill
1	0	0	conventional driving, odd gear engaged
1	0	1	hybrid driving
1	1	0	take-off, charge during driving

$$T_w = r^w_{ice}T_{ice} + r^w_{em}T_{em} \quad (2)$$
$$r^w_{ice} = R_{f_{(R_1)}}R_1C_1 + R_{f_{(R_2)}}R_2C_2 \quad (3)$$
$$r^w_{em} = R_{f_{(R_1C_1C_2+R_2)}}\left(R_1C_1C_2 + R_2\right)rat_{em} \quad (4)$$
$$\omega_{ice} = r^w_{ice}\frac{v}{R_w} + \left(1 - C_1 - N_2C_2\right)\omega^{ctrl}_{ice} \quad (5)$$
$$\omega_{em} = r^w_{em}\frac{v}{R_w} + rat_{em}C_2\left(1 - C_1\right)\left(1 - N_2\right)\omega^{ctrl}_{ice} \quad (6)$$

The battery SOC is the only considered state of the system, for which an internal resistance model has been retained in this paper. Its dynamics is described by the integrator-like relation below, involving its open circuit voltage (OCV), internal resistance (R), battery capacity (Q_{max}).

$$S\dot{O}C = -\frac{OCV_{(SOC)} - \sqrt{OCV^2_{(SOC)} - 4R_{(SOC)}P_b}}{2R_{(SOC)}Q_{max}} \quad (7)$$

where $P_b = \frac{\pi}{30}\omega_{em}T_{em} + loss\left(\omega_{em}, T_{em}\right)$ is the battery power.

The engine fuel rate is given as a non linear map with respect to torque and rotational speed, but in view of control design, an analytical expression with an explicit appearance of the control variable, is needed. The vehicle considered for this case-study is equipped with a turbo-charged 1.2 L SI engine, whose fuel rate dependence on torque is illustrated in Fig. 2, via a parametrization of curves with respect to ω_{ice}. In this paper, a piecewise linear approximation with respect to torque is introduced, as expressed below:

$$\dot{m}_f = \alpha_j(\omega_{ice})T_{ice} + \beta_j(\omega_{ice}), \quad \text{for } j = 1 \ldots N_{part} \quad (8)$$

where N_{part} is the number of torque partitions.

3. MPC- BASED ENERGY MANAGEMENT

The focus of this work is the optimization-based decision making for torque distribution between the engine and the electric machine with respect to fuel consumption, for a